Journal of Cleaner Production 223 (2019) 928–945

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Stochastic multi-objective decision making for sustainable irrigation in a changing environment

Mo Li [a], Qiang Fu [a, *], Ping Guo [b], Vijay P. Singh [c], Chenglong Zhang [b], Gaiqiang Yang [d]

[a] School of Water Conservancy & Civil Engineering, Northeast Agricultural University, Harbin, Heilongjiang, 150030, China
[b] Centre for Agricultural Water Research in China, China Agricultural University, Beijing, 100083, China
[c] Department of Biological and Agricultural Engineering & Zachry Department of Civil Engineering, Texas A & M University, 321 Scoates Hall, 2117 TAMU, College Station, TX, 77843-2117, USA
[d] Institute of Environmental Science, Taiyuan University of Science and Technology, Taiyuan, Shanxi, 030024, China

ARTICLE INFO

Article history:
Received 4 November 2017
Received in revised form
14 March 2019
Accepted 15 March 2019
Available online 18 March 2019

Keywords:
Stochastic multi-objective
Irrigation water allocation
Modelling
Sustainability
Changing environment

ABSTRACT

Agricultural water scarcity is a global problem and effective management of limited water resources for irrigation to meet socioeconomic demands for sustainable development is a huge challenge. A stochastic multi-objective non-linear programming (SMONLP) model is developed for the identification of sound irrigation water allocation schemes. The SMONLP model improves upon previous methods by tackling contradictions of society-economy-resources as well as reflecting uncertainty expressed as probability distributions in an agricultural irrigation system. The SMONLP model permits in-depth analyses of various water allocation policies that are associated with different levels of water supply and climate change. The developed SMONLP model is applied to optimal irrigation allocation in a semi-arid river basin in China. Results reveal that the model coordinates the regulation of interactions of society-economy-resources by balancing the targets of water productivity, allocation equity, profit, economic benefit risk, blue water utilization, and leakage loss. Moreover, surface water availability associated with different violation risk probabilities can lead to the changes in comprehensive benefit of society-economy-resources and irrigation shortages. Nearly each of the 17 irrigation regions suffers from water deficit, because water is insufficient to satisfy the requirement of crops, however, the degree of water shortage is gradually weakened when flow level ranges from low to high. The coordination degree is also used to evaluate the sustainability of water allocation and the results of comparison show that the irrigation water allocation under RCP 4.5 presents lower coordination of society-economy-resources which are mainly attributed to the aggravated contradiction between water supply and demand. A real world study demonstrates the practicability of the developed model, allowing the river basin authorities to determine irrigation water allocation strategies in a changing environment, thus promoting sustainable development of agricultural irrigation systems.

1. Introduction

A major socio-economic and global sustainability issue is the increasing severity of water shortages due to increasing demands and decreasing supplies (Abdulbaki et al., 2017). Agriculture is the biggest water consumer of water resources and more water is needed for irrigation to increase food production for the burgeoning global population. However, water is transferred from low-value agricultural irrigation to high-value users, such as domestic, industrial and hydroelectric (Liu et al., 2017). Besides, the low efficiency of irrigation water utilization and less than up-to-date management of agricultural irrigation systems intensify irrigation water crisis, putting additional stress on the performance of agriculture. Such problems are particularly acute in primarily agricultural countries, such as China. Therefore, optimal management of agricultural irrigation is a potential way to mitigate water shortages, thus promoting agricultural water management.

Irrigation management through optimization modelling has received considerable attention for identifying effective irrigation

* Corresponding author. School of Water Conservancy & Civil Engineering, Northeast Agricultural University, Changjiang Street No. 600, Harbin, 150030, PR China.

E-mail address: fuqiang@neau.edu.cn (Q. Fu).

https://doi.org/10.1016/j.jclepro.2019.03.183
0959-6526/

water allocation strategies (Norry et al., 2012; Singh, 2014; Yang et al., 2015; Ren et al., 2017). Many studies have optimized irrigation water resources with the aim of maximizing crop yield or consequent benefits (Georgiou and Papamichail, 2008; Guo et al., 2014). However, agricultural irrigation systems are complex due to the interactions among natural resources, social, economic and ecological environment elements. For sustainable development of agricultural irrigation systems, irrigation management, comprehensively considering these elements, is needed. Sustainable development entails the tradeoff in balancing the benefit from both social and economic dimensions satisfying the water requirement of ecological environment through effective utilization of limited water resources without influencing the development of future generations (Cai et al., 2002; Li et al., 2019). To this end, multi-objective programming models have received much attention.

Some researchers have dealt with sustainable management of agricultural irrigation systems using multi-objective programming. For example, Fasakhodi et al. (2010) optimized sustainability indicators expressed as "net return/water consumption" and "labor employment/water consumption" using a multi-objective fractional goal programming in an agricultural irrigation system. Gurav and Regulwar (2012) presented a multi-objective sustainable irrigation planning model maximizing the net benefit, crop production, employment generation, and manure utilization. Li et al. (2017) proposed a fuzzy multi-objective non-linear programming to optimally allocate irrigation water resources balancing the objectives of crop yield, water cost, and water utilization. However, more elements associated with society, economy, and resources need to be considered in order to more efficiently resolve conflicts in agricultural irrigation systems. For example, although crop yield can be regarded as an indicator of social benefit through satisfying food security, agricultural water managers aspire to improve irrigation efficiency rather than simply increase crop production especially in arid and semi-arid regions that have severe water shortages. Additionally, for large agricultural irrigation systems, the equitable access to irrigation water, which is closely related to social stability, is critical for eradicating poverty. Besides net profit, the risk of diminishing economic returns attributed to the variation in water availability should also be considered to better reflect the economic benefit. Further, irrigation water-saving as well as leakage loss should be taken into account to improve water utilization efficiency. However, few studies have simultaneously considered these elements associated with society, economy and resources to seek participatory management options for the sustainable utilization of water resources in agricultural irrigation systems.

In agricultural irrigation systems, optimal water resources allocation schemes vary in response to the temporal changes of available water resources (Zhang and Guo (2018); Li et al., 2018). Such schemes can be based on stochastic mathematical programming wherein parameters in the objective function or constraints are represented by probability distributions. A major type of stochastic programming is chance constrained programming (CCP) which requires that all of the constraints be satisfied in a proportion of cases under given probability levels and is effective for optimization where the right-hand-side coefficients are random (Guo and Huang, 2009; Guo et al., 2010). In order to evaluate the impact of fluctuations of irrigation water availability on irrigation allocation schemes, incorporating CCP into the multi-objective programming model for sustainable irrigation management is essential, but has rarely been considered in the literature. Besides, irrigation water allocation is under constant threat from changing environment mainly embodying climate change and human activities. Climate change seems to have shifted the balance of water supply and water demand, and thus affects irrigation water allocation. Specifically, climate change affects water supply mainly attributing to the changes in precipitation and temperature (Kang et al., 2009). And meanwhile, climate change affects irrigation water demand via physiology and phenology, effective precipitation, evapotranspiration and soil water balances (Shahid, 2011). Impact of human activities on irrigation water allocation includes withdrawal of water from both rivers and aquifer through hydraulic engineering, and man-made changes in land use and water-saving measures. How optimal irrigation water schemes change with reliability of satisfying (or risk of violating) water availability constraints being considered in a changing environment has captured the attention of decision makers.

In a changing environment, different scenarios such as different flow levels, risk confidence levels, importance levels of different targets, different climate conditions, etc. will directly and significantly cause changes of various irrigation water allocation schemes. Among various schemes of irrigation water allocation, choosing the schemes that are optimal is another issue that decision makers are interested in. Optimal schemes can be identified by evaluating various schemes. Among many evaluation methods, the synergy theory has been found as an effective way to evaluate the sustainability of water resources allocation schemes by studying the degree of coordination of each dimension of a society-economic-resources system (Li et al., 2015a; Zhao et al., 2017). However, the system of indicators used in the previous studies often involve indicators with no connection with optimal irrigation allocation, leading to a water-insensitive evaluation result. In order to solve this problem, the indicators of each dimension associated with society, economy and resources should be representative and have a direct relationship with changes of water allocation. Hence, all the objective function values of the multi-objective programming model will be considered as indicators based on the optimal irrigation water allocations in a changing environment to clearly evaluate the sustainability of agricultural irrigation systems. However, such an analysis for optimal irrigation water allocation schemes has rarely been done.

The objective of this study therefore is to develop a stochastic multi-objective non-linear programming (SMONLP) model for sustainable irrigation management in response to the above challenges. The SMONLP model will incorporate CCP into a multi-objective linear/nonlinear programming framework to cope with uncertainties expressed through probability distributions. The objective of the SMONLP model is to achieve the optimal comprehensive benefit of irrigation productivity promotion, irrigation equity, net profit increase, economic benefit loss risk, blue water saving, and leakage loss reduction. The SMONLP model will be applied to allocate limited surface water and groundwater resources to different subareas in the middle reaches of Heihe River basin, northwest of China. Results of different irrigation allocations will be generated by considering the fluctuation of water availability and climate change, and then, the sustainability of these results will be evaluated. Results of this study will offer insights into the tradeoff among system comprehensive benefit, irrigation strategy, and agriculture sustainability.

2. Problem description and formulation of models

2.1. Overview of the problem

In an irrigation water allocation process, the available water resources consisting of both river water and groundwater will be allocated to each subarea of an irrigation-dominated river basin in which water resource is one of the major restrictions to the basin's development. Water allocation to different subareas may result in different development modes. In order to improve the sustainable

development of a river basin, benefits of society, economy and resources utilization should be considered simultaneously in order to assure ecological water utilization. For societal benefit, maximizing crop water productivity (WP) and minimizing the Gini coefficient are the main objectives. WP is defined as the ratio of the mass of crop yield to the volume of water consumed. WP is a key term in the evaluation of deficient irrigation strategies (Geerts and Raes, 2009). Increasing WP is particularly appropriate where water is scarce compared with other resources involved in production and it can be considered as a reflection of social benefit. The Gini coefficient is a measure of resource distribution inequality and it is an important measure of social stability (Hu et al., 2016; Dai et al., 2018). For economic benefit, maximizing net profit and minimizing economic benefit loss risk are the main objectives. Net profit is the direct reflection of economic benefit. Economic benefit loss risk can help decision makers learn the risk of water management system failure due to the fluctuation in available water and water demand influenced by changes of natural conditions and human activities. For resources utilization, minimizing blue water utilization rate and minimizing leakage loss are the main objectives. Irrigated agriculture uses both green water and blue water. Blue water contains water from rivers, lakes and groundwater, and green water is defined as the soil water in the unsaturated zone derived from precipitation (Rost et al., 2008). Green water should be utilized fully if possible so that more blue water can be saved which can be directly used by socio-economic sectors. Therefore, minimizing blue water contributes to water-saving and irrigation efficiency improvement. Minimizing irrigation leakage loss is another optimization method for saving water. Such objectives are especially suitable for arid and semi-arid areas which have water shortages. The above objectives should be subject to constraints of available water supply of both surface water and groundwater, water allocation consistency, water conveyance, water transformation, economic risk, food security, and water demand.

In the allocation process, available water is one of the key parameters for optimal allocation with fluctuation characteristics under different flow levels. Water availability is stochastic following a certain kind of distribution corresponding to different probabilities. Realizing the changing of water allocation schemes under different probabilities is necessary for decision makers to make adjustments of water allocation policy accordingly. On this basis, how to balance conflicting benefits in a changing environment in order to improve sustainable development of an irrigation-dominated river basin is a challenge for decision makers. A number of irrigation water allocation schemes under various scenarios will be obtained through optimization decision-making. In addition to comparing the changes of different schemes, decision makers attach more attention to schemes which should be chosen under different environments. This study focuses on the sustainable development of the command area. Therefore, the degree of coordination which reflects the mutual compatibility of interrelated subsystems (social dimension, economic dimension, and water resources dimension in this study) can be considered as a measure to determine the optimal scheme. The decision making framework is depicted in Fig. 1.

2.2. Formulation of models

A stochastic multi-objective non-linear programming (SMONLP) model is developed by considering social benefit, economic benefit and resources utilization in order to optimize irrigation water allocation in time and space in a changing environment. Notations of the mathematical formulations are presented in Table 1.

2.2.1. Objective function

The SMONLP model includes six objectives: (1) maximization of WP; (2) minimization of Gini coefficient; (3) maximization of net profit; (4) minimization of economic benefit loss risk; (5) minimization of blue water utilization rate; and (6) minimization of leakage loss. Objectives (1) and (2) represent social benefit, objectives (3) and (4) represent economic benefit, and objectives (5) and (6) represent water resources utilization conditions. This paper considers the expected values of different flow levels for each objective function. Therefore, the expected value model of stochastic variables/parameters is integrated in objective functions as substitutes to illustrate the underlying uncertainty. In order to simplify the operation of the optimization model, the distributions of random variables/parameters in the objective functions are assumed to be approximated by a discrete function with occurrence probabilities (p_h) of different flow levels, while the randomness of water availability in the constraint is expressed through CCP. Each of these objectives is now discussed.

2.2.1.1. Maximizing water productivity. WP is defined as the ratio of the mass of crop yield to the volume of water consumed. In water-scarce regions, high WP should be preferred. Water consumed, in this study, equals the summation of net irrigation amounts of both surface water and groundwater and effective precipitation. This objective function can be expressed as

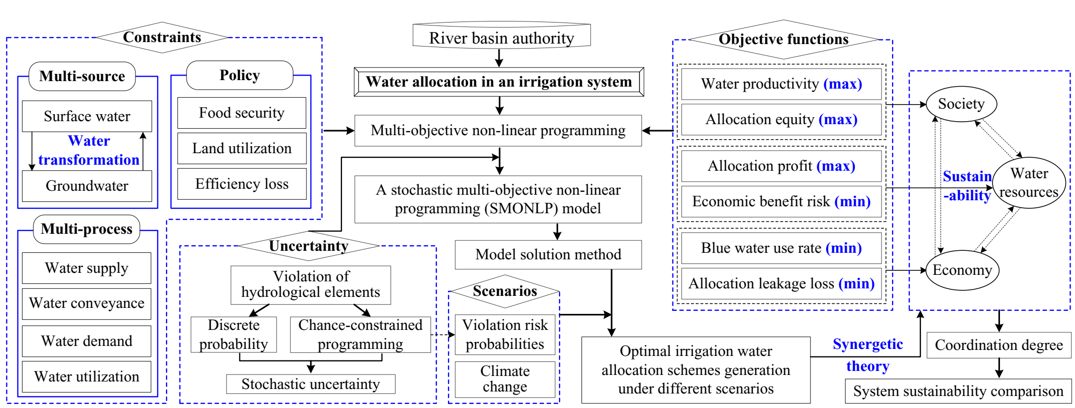

Fig. 1. Decision making framework of sustainable irrigation management.

Table 1
Notations of the SMONLP model.

Indices	Definitions
i	Index of subarea ($i = 1, 2, \cdots, I$)
t	Index of period ($t = 1, 2, \cdots, T$)
h	Index of flow levels ($h = 1, 2, \cdots, H$)
sur	Superscript of surface water
gro	Superscript of groundwater
$canal$	Superscript of canal irrigation
$field$	Superscript of field irrigation
max	Superscript of maximum
min	Superscript of minimum
Variables	
x_{ith}^{sur}	Gross surface water irrigation for subarea i in period t under flow level h (m^3)
x_{ith}^{gro}	Gross groundwater irrigation for subarea i in period t under flow level h (m^3)
$S_{i(t-1)h}^{sur}$	Residual water for subarea i in period $t-1$ under flow level h (m^3)
W_{ith}^{sur}	Surface water availability for subarea i in period t under flow level h (m^3)
W_{ith}^{gro}	Groundwater availability for subarea i in period t under flow level h (m^3)
V_h	Auxiliary variables under hydrological year h
ξ_α	The maximum economic efficiency loss at the $1-\alpha$, auxiliary variables
Parameters	
WP	Water productivity (kg/m^3)
YAF_i	Actual yield per unit area of food crops for subarea i (kg/ha)
YAC_i	Actual yield per unit area of commercial crops for subarea i (kg/ha)
p_h	Occurrence probability of flow level h
AF_{ih}	Irrigation area of food crops for subarea i under flow level h (ha)
AC_{ih}	Irrigation area of commercial crops for subarea i under flow level h (ha)
ep_{ith}	Effective precipitation for subarea i in period t under flow level h (m^3)
η_i^{canal}	Water utilization coefficient of canal irrigation for subarea i
η_i^{field}	Water utilization coefficient of field irrigation for subarea i
$Gini$	Gini coefficient
B_i	Benefit per unit yield for subarea for subarea i (Yuan/kg)
Y_i	Actual crop yield per unit water amount of irrigation for subarea i (kg/m^3)
CM_i^{sur}	Management cost of surface water for subarea i ($Yuan/m^3$)
CM_i^{gro}	Management cost of groundwater for subarea i ($Yuan/m^3$)
CS^{sur}	Supply cost for surface water ($Yuan/m^3$)
CS^{gro}	Supply cost for groundwater ($Yuan/m^3$)
α	Significance level
$\Pr\{\}$	The CCP constraint
p_v	Violation probability of CCP constraint
VWC_{ith}	Virtual water content for subarea i in period t under flow level h (m^3)
TW_{ih}^{sur}	Total surface water availability for subarea i under flow level h (m^3)
Q_i'	Minimum water conveyance flow for subarea i (m^3/s)
Q_i	Maximum water conveyance flow for subarea i (m^3/s)
T_t	Filling time (s)
TW_{ih}^{gro}	Total surface water availability for subarea i under flow level h (m^3)
θ_c	Canal seepage coefficient
θ_{ep}	Precipitation seepage coefficient
Δh_{it}	Water level differences for subarea i in period t (m)
μ_i	Specific yield of the aquifer for subarea i
$L_h(x_{ith}^{sur}, x_{ith}^{gro})$	Benefit loss function
b_i	Benefit per unit water amount ($Yuan/m^3$)
WD_{ith}	Water demand for subarea i in period t under flow level h (m^3)
FD	Minimum grain demand per capital (kg/per capital)
PO_i	Population of subarea i
IR_{ith}	Net minimum water demand for subarea i in period t under flow level h (m^3)

Note: Yuan is the monetary unit of China.

$$\max WP = \frac{\sum_{i=1}^{I}\sum_{h=1}^{H} p_h (YAF_i \cdot AF_{ih} + YAC_i \cdot AC_{ih})}{\sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{h=1}^{H} p_h \left(x_{ith}^{sur} \cdot \eta_i^{canal} \cdot \eta_i^{field} + x_{ith}^{gro} \cdot \eta_i^{field} + ep_{ith}\right)} \tag{1}$$

2.2.1.2. Minimizing gini coefficient. The Gini coefficient measures the inequality among values of a frequency distribution and it ranges from 0 to 1. For irrigation water allocation, a smaller Gini coefficient means the allocation is more even. Especially, a Gini coefficient of zero describes perfect equality, where all values are the same and a Gini coefficient of 1 expresses maximal inequality among values. The Gini coefficient can be calculated according to Lorenz curve shown in Fig. 2. Gini coefficient = (Area A)/(Area A + Area B). In terms of this study, the objective function can be expressed as

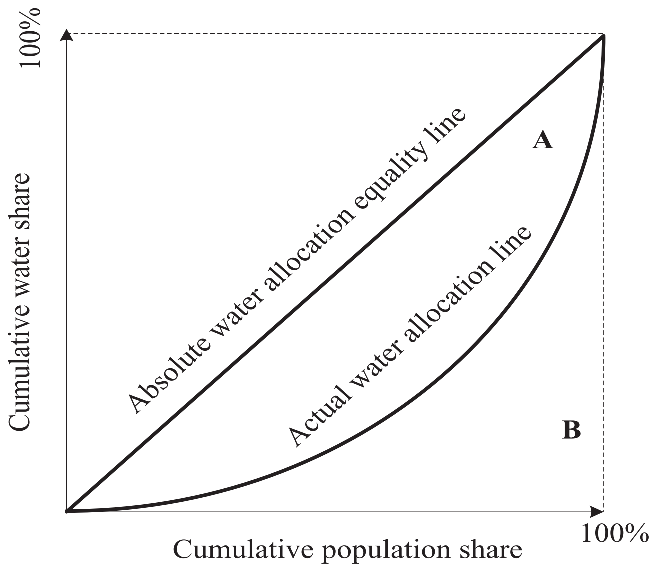

Fig. 2. Lorenz curve.

$$\min Gini = \frac{1}{2I\sum\limits_{i=1}^{I}\sum\limits_{t=1}^{T}\sum\limits_{h=1}^{H} p_h \frac{\left(x_{ith}^{sur}+x_{ith}^{gro}+ep_{ith}\right)}{PO_i}} \sum_{l=1}^{I} \times \sum_{k=1}^{I} \left| \frac{\sum\limits_{t=1}^{T}\sum\limits_{h=1}^{H} p_h\left(x_{lth}^{sur}+x_{lth}^{gro}+ep_{lth}\right)}{PO_l} - \frac{\sum\limits_{t=1}^{T}\sum\limits_{h=1}^{H} p_h\left(x_{kth}^{sur}+x_{kth}^{gro}+ep_{kth}\right)}{PO_k} \right| \quad (2)$$

2.2.1.3. Maximizing profit. Total profit equals total revenue minus costs, including cost of management and cost of water supply. This objective function can be expressed as

$$\max Profit = \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{h=1}^{H} p_h \left[\begin{array}{l} B_i \cdot Y_i\left(x_{ith}^{sur}\cdot\eta_i^{canal}\cdot\eta_i^{field} + x_{ith}^{gro}\cdot\eta_i^{field}\right) \\ -\left(CM_i^{sur}x_{ith}^{sur}+CM_i^{gro}x_{ith}^{gro}\right) - \left(CS^{sur}x_{ith}^{sur}+CS^{gro}x_{ith}^{gro}\right) \end{array} \right] \quad (3)$$

2.2.1.4. Minimizing economic benefit risk. In irrigation water allocation process, the fluctuation in water availability is the main source of uncertainty involved in water allocation and can generate the corresponding risk of economic efficiency loss. Generally, high risk is positively correlated with high returns, but in the meanwhile will cause high losses. Because if actual water availability is lower than expected, the actual benefit will fall short of the promised benefit. Then decision makers may identify more expensive ways to obtain more water to make up the economic losses such as buying water from adjacent and well-watered regions or exploring groundwater within the exploitable capacity of groundwater. Therefore, a high variability in water availability aggravates the risk of water management system failure which poses a problem for decision makers. As a result, the economic efficiency loss risk control is a valid and viable solution (Hu et al., 2016), and the conditional vale-at-risk (CVaR) can be used to shape the economic benefit loss risk. CVaR is known as mean excess loss and is widely used in portfolio selection for risk-aversion in economic decision making. CVaR is the conditional expected value when the losses exceed the risk value and it is an improvement on value-at-risk (VaR) which represents a maximum loss. CVaR is defined as (Rockafellar and Uryasev, 2000)

$$\mathrm{CVaR}(Z) = E(Z|Z \ge VaR_\alpha(Z)) \quad (4)$$

where Z is a stochastic variable; α is the predefined significance level, and $\alpha\in[0,1]$; $\mathrm{VaR}_\alpha(Z)$ is the value-at-risk at the significance level α and it is expressed as $\inf\{\eta\in\mathbb{R}: \ F_Z(\eta)\ge\alpha\}$ with $F_Z()$ representing the cumulative distribution function of stochastic variable Z. To facilitate the calculation, CVaR with significance level α can be expressed as (Li et al., 2015b)

$$\mathrm{CVaR}_\alpha(Z) = \inf_{\eta\in R}\left\{\eta + \frac{1}{1-\alpha}E([Z-\eta]_+)\right\} \quad (5)$$

where $[Z-\eta]_+ = \max\{0,\ Z-\eta\}$, and $(Z-\eta)\in\mathbb{R}$.

Based on the above principle, the objective function of economic benefit loss risk can be expressed as

$$\min Risk = \xi_\alpha + \frac{1}{1-\alpha}\sum_{h=1}^{H} p_h V_h \quad (6)$$

2.2.1.5. Minimizing blue water utilization rate. The blue water utilization rate is the ratio of net surface water and groundwater to the virtual water content (*VWC*) of crops (Su et al., 2014; Zhi et al., 2016). This constraint can be expressed as

$$\min Blue\ \ water = \frac{\sum\limits_{i=1}^{I}\sum\limits_{t=1}^{T}\sum\limits_{h=1}^{H} p_h\left(x_{ith}^{sur}\cdot\eta_i^{canal}\cdot\eta_i^{field}+x_{ith}^{gro}\cdot\eta_i^{field}\right)}{\sum\limits_{i=1}^{I}\sum\limits_{t=1}^{T}\sum\limits_{h=1}^{H} p_h\cdot VWC_{ith}} \quad (7)$$

2.2.1.6. Minimizing leakage loss. Irrigation leakage losses contain leakage losses from canals which are associated with surface water irrigation and leakage losses from field which are associated with both surface water and groundwater.

$$\min\ Leakage\ \ loss = \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{h=1}^{H} p_h x_{ith}^{sur}\left(1-\eta_i^{canal}\right) + \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{h=1}^{H} p_h\left[\left(x_{ith}^{sur}+x_{ith}^{gro}\right)\left(1-\eta_i^{field}\right)\right] \quad (8)$$

2.2.2. Constraints

The above six objective functions are subject to the following constraints.

2.2.2.1. Surface water availability. Water allocated to various irrigation areas must not exceed the surface water availability of each time period under each flow level. Usually, there is no detailed information about the surface water availability for each subarea in each time period under each flow level. But surface water availability for each subarea under each flow level is available, based on local planning reports. Therefore, the summation is done over the period from the day of crop planting to the day of harvest and then equation (10) can be written. In addition, decision makers would like to know how irrigation water optimal allocation schemes change when available surface water changes within permissible levels, and CCP is effective in handling this problem. CCP requires that all of the constraints be satisfied in proportion of cases under given probability levels. Then equation (10) is an uncertain constraint expressed as CCP.

$$x_{ith}^{sur} \leq W_{ith}^{sur} + S_{i(t-1)t}^{sur} \qquad \forall i,t,h \tag{9}$$

$$\Pr\left\{ \sum_{t=1}^{T} W_{ith}^{sur} \leq TW_{ih}^{sur} \right\} \geq 1 - q_v \qquad \forall i,h \tag{10}$$

2.2.2.2. Water allocation consistency constraint. Water allocation consistency reflects the connection of water allocation in adjacent time intervals. Specifically, the surplus water of a certain time period equals the sum of water that runs into the command area minus allocated water and the surplus water of the last time period. Water allocation consistency can save water by making the best of surplus water resources. This constraint can be expressed as

$$S_{i(t-1)h}^{sur} = S_{i(t-2)h}^{sur} + W_{i(t-1)h}^{sur} - x_{i(t-1)h}^{sur} \qquad \forall i,t,h \qquad S_{i1h}^{sur} = 0 \tag{11}$$

$$L_h\left(x_{ith}^{sur}, x_{ith}^{gro}\right) = 1 - \left\{ \frac{\sum_{i=1}^{I}\sum_{t=1}^{T} b_i\left[WD_{ith} - \left(x_{ith}^{sur}\cdot\eta_i^{canal}\cdot\eta_i^{field} + x_{ith}^{gro}\cdot\eta_i^{field} + ep_{ith}\right)\right]}{\sum_{i=1}^{I}\sum_{t=1}^{T} b_i\left(WD_{ith} + ep_{it}\right)} \right\} \qquad \forall h \tag{17}$$

2.2.2.3. Water conveyance constraint. Water conveyance constraint is an engineering constraint which ensures that surface water allocation satisfies the flow's design requirement of diversion canal of each irrigation area in different water allocation periods. This constraint can be expressed as

$$Q_i^{'}\cdot T_t \leq x_{ith}^{sur} \leq Q_i\cdot T_t \ \forall i,t,h \tag{12}$$

2.2.2.4. Groundwater water availability. Similar to surface water, groundwater allocation must not exceed the available groundwater supply to protect groundwater environment. The exploitable quantity of groundwater is affected by both hydrological cycle and technological conditions on the basis of guaranteeing groundwater eco-environment. Usually, the changes of groundwater availability are not as conspicuous as surface water availability under different flow levels, especially for regions that are irrigated mainly by surface water. Therefore, in this study, CCP is not applied to groundwater water availability constraint. This constraint can be expressed as

$$x_{ith}^{gro} \leq W_{ith}^{gro} \qquad \forall i,t,h \tag{13}$$

$$\sum_{t=1}^{T} W_{ith}^{gro} \leq TW_{ih}^{gro} \qquad \forall i,h \tag{14}$$

2.2.2.5. Water transformation constraint. Water transformation constraint reflects the mutual conversion between surface water, groundwater and effective precipitation. This constraint reflects the hydrological balance of the groundwater aquifer which will help the groundwater table remain at a predetermined level. The constraint can be expressed as

$$x_{ith}^{gro} - \left\{\theta_c\cdot x_{ith}^{sur} + \left(1-\eta_i^{field}\right)\left[(1-\theta_c)x_{ith}^{sur} + x_{ith}^{gro}\right] + \theta_{ep}\cdot ep_{it}\right\} \leq \Delta h_{it}\cdot\mu_i \qquad \forall i,t,h \tag{15}$$

2.2.2.6. Risk constraint. The risk constraint corresponds to the economic benefit loss risk objective (equation (7)) with economic efficiency loss function embedded. The economic efficiency loss function can be defined as the economic return divided by the maximum potential economic return (Divakar et al., 2011; Hu et al., 2016).

$$L_h\left(x_{ith}^{sur}, x_{ith}^{gro}\right) - \xi_\alpha - V_h \leq 0 \tag{16}$$

$$WD_{ith} = k_c(ET_0)_{ith} \qquad \forall i,t,h \tag{18}$$

2.2.2.7. Food security constraint. For any irrigation area, food production should satisfy the minimum food requirement of each irrigation area to guarantee people's living standards. This constraint can be expressed as

$$Y_i\sum_{t=1}^{T}\left(x_{ith}^{sur}\cdot\eta_i^{canal}\cdot\eta_i^{field} + x_{ith}^{gro}\cdot\eta_i^{field}\right) \geq FD\cdot PO_i \qquad \forall i,h \tag{19}$$

2.2.2.8. Water demand constraint. Irrigation requirement during the period of growth of all crops should be satisfied by effective precipitation, available surface water, and groundwater resources. The constraint can be expressed as

$$\left(x_{ith}^{sur}\cdot\eta_i^{canal}\cdot\eta_i^{field}+x_{ith}^{gro}\cdot\eta_i^{field}+ep_{ith}\right)\geq IR_{ith}\qquad\forall i,t,h \tag{20}$$

2.2.2.9. Non-negative constraint. All the decision variables, including surface water and groundwater allocations, surplus water, surface and groundwater availability to each irrigation region in each time period under each flow level, and the auxiliary variables under different flow levels should not be negative.

$$x_{ith}^{sur}\geq 0\quad\forall i,t,h \tag{21}$$

$$x_{ith}^{gro}\geq 0\quad\forall i,t,h \tag{22}$$

$$S_{ith}^{sur}\geq 0\quad\forall i,t,h \tag{23}$$

$$W_{ith}^{sur}\geq 0\quad\forall i,t,h \tag{24}$$

$$W_{ith}^{gro}\geq 0\quad\forall i,t,h \tag{25}$$

$$V_h\geq 0\qquad\forall h \tag{26}$$

2.3. Method of solution

2.3.1. Chance constrained programming

When some right-hand-side parameters are stochastic and can be represented as probability distributions, the CCP method can be applied. Water availability is a stochastic parameter and applying CCP to surface availability constraint will help decision makers realize the changing trend under different violations of probabilities. When applying CCP, not all of the constraints must be totally satisfied so that the reliability of satisfying or the risk of violating individual constraints can be effectively reflected (Sun et al., 2013). A typical CCP model can be expressed as follows (Huang, 1998):

$$\min f(X) \tag{27}$$

subject to

$$\Pr[A_i(t)X\leq b_i(t)]\geq 1-p_i\qquad i=1,2,\cdots,m \tag{28}$$

$$X\geq 0 \tag{29}$$

where $A_i(t)\in A(t)$, $b_i(t)\in B(t)$, $t\in T$; $A(t)$ and $B(t)$ are sets with random elements defined on a probability space T; $p_i(p_i\in[0,1])$ is a given level of probability for constraint i; and m is the number of constraints.

In this study, because of the randomness of parameters on right-hand-side of the constraint, constraint (28) is an uncertain constraint. When the left-hand-side coefficients (elements of $A_i(t)$) are deterministic, constraint (28) is linear and the set of feasible constraints is convex (Zhu and Huang, 2011):

$$A_iX\leq b_i(t)^{(p_i)},\qquad i=1,2,\cdots,m \tag{30}$$

where $b_i(t)^{(p_i)}=F^{-1}(p_i)$, and $F^{-1}(p_i)$ is the cumulative distribution function of b_i; p_i is the given probability of violating constraint i. Thus, the CCP method can be used to solve problems with stochastic right-hand sides by converting them into deterministic versions through: (a) fixing a certain level of probability p_i for uncertain constraint i, and (b) imposing that constraint should be satisfied with at least a probability level of $1-p_i$.

2.3.2. Weighted minimum deviation method

The SMONLP model can be solved by the minimum deviation method. The main advantage of the minimum deviation method is that it only requires local information of decision making, that is, the optimal solution of each objective functions (Li and Guo, 2014). The essence of this multi-objective solution is to transform the multi-objective programming into single-objective programing through normalization of each objective to eliminate the effect of the scale of objective function values. Generally, the minimum deviation method can be expressed as

$$\min F'(X)=\sum_{i=1}^{l}\frac{f_i(X)-f_i^{\min}}{f_i^{\max}-f_i^{\min}}+\sum_{j=l+1}^{m}\frac{f_j^{\max}-f_j(X)}{f_j^{\max}-f_j^{\min}} \tag{31}$$

where $f_i(X)$ $(i=1,2,\cdots,l)$ represent the minimum objective functions and $f_j(X)$ $(j=l+1,l+2,\cdots,m)$ represent the maximum objective functions. $f_i^{\max}$, $f_i^{\min}$ are the maximum and minimum values of $f_i(X)$, and $f_j^{\max}$, $f_j^{\min}$ are the maximum and minimum values of $f_j(X)$. In order to obtain the optimal solution of $F'(X)$, the values of $f_i^{\max},f_i^{\min}$ and $f_j^{\max},f_j^{\min}$ should not be equal.

When considering the importance of different objectives, the weighting method can be adopted (Hu et al., 2016). Then, the transfer forms of the SMONLP model developed in this study can be written as

$$\min F'(X)=\min\left\{\begin{array}{l}\omega_1\left(\dfrac{f_1^{\max}-f_1}{f_1^{\max}-f_1^{\min}}\right)+\omega_2\left(\dfrac{f_2-f_2^{\min}}{f_2^{\max}-f_2^{\min}}\right)+\omega_3\left(\dfrac{f_3^{\max}-f_3}{f_3^{\max}-f_3^{\min}}\right)\\+\omega_4\left(\dfrac{f_4-f_4^{\min}}{f_4^{\max}-f_4^{\min}}\right)+\omega_5\left(\dfrac{f_5-f_5^{\min}}{f_5^{\max}-f_5^{\min}}\right)+\omega_6\left(\dfrac{f_6-f_6^{\min}}{f_6^{\max}-f_6^{\min}}\right)\end{array}\right\} \tag{32}$$

where ω_1, ω_2, ω_3, ω_4, ω_5 and ω_6 are the weights for objectives f_1, f_2, f_3, f_4, f_5 and f_6, respectively, and $\omega_1+\omega_2+\omega_3+\omega_4+\omega_5+\omega_6=1$.

2.3.3. Solution steps for SMONLP model

The key to solve the SMONLP model is to transform the uncertain and multi-objective programming model into a deterministic and single-objective programming model. A detailed solution process can be summarized as follows:

Step 1 Model the SMONLP.

Step 2 Convert the stochastic constraints into deterministic forms by the CCP method with the given probability q_v under each flow level.
Step 3 Solve the SMONLP model by considering one objective function at a time and ignoring all others. Repeat the process six times for the six objective functions. Find the optimal solutions and the minimum and maximum values of the six functions.
Step 4 Solve the SMONLP model based on the minimum deviation method given different weights for the six objective functions.
Step 5 Repeat steps 2–4, corresponding to different q_v.
Step 6 Generate solutions under different scenarios.

2.4. Evaluation scheme

Among various optimal water allocation schemes under different scenarios, which scheme should be chosen is what the decision maker desires. An index of coordination degree can be adopted to evaluate the various generated schemes based on the harmonious development of dimensions of society, economy, and water resources utilization (Zhao et al., 2017). The concept of coordination degree arose from the synergetic theory. According to this theory, the subsystems and the properties of parameters in the system are different and unbalanced. The parameters are divided into fast parameters and slow parameters, based on this characteristic. When the system is approaching the critical point, the slow parameters, known as order parameters, dominate the evolution process rather than the fast parameters (Li et al., 2015a). To measure the synergy of all the order parameters, the index of order degree can be introduced.

Let the order parameters of subsystem S_j be $e_j = (e_{j1}, e_{j2}, \cdots, e_{jn})$, $n \geq 1$, and $\beta_{ji} \leq e_{ji} \leq \alpha_{ji}$, $i \in [1, n]$, with α_{ji} and β_{ji} representing the maximum and minimum values of e_{ji}, respectively. Assuming that the larger the $e_{j1}, e_{j2}, \cdots, e_{jm}$ $(1 \leq m \leq p)$, the higher the order degree, the larger the $e_{jm+1}, e_{jm+2}, \cdots, e_{jp}$ $(m \leq p \leq n)$, the lower the order degree, and the closer $e_{jp+1}, e_{jp+2}, \cdots, e_{jn}$ to constant c, the higher the order degree. The formula of order degree of each order parameter can be expressed as follows (Huang and Chang, 2007):

$$u_j(e_{ji}) = \begin{cases} \left(e_{ji} - \beta_{ji}\right) \Big/ \left(\alpha_{ji} - \beta_{ji}\right) & i \in [1, m] \\ \left(\alpha_{ji} - e_{ji}\right) \Big/ \left(\alpha_{ji} - \beta_{ji}\right) & i \in [m+1, p] \\ 1 - \left(e_{ji} - c\right) \Big/ \left(\alpha_{ji} - \beta_{ji}\right) & i \in [p+1, n] \end{cases} \tag{33}$$

where $u_j(e_{ji})$ is the order degree of order parameter e_{ji}, and $u_j(e_{ji}) \in [0, 1]$.

Based on the order degree, the coordination degree can be obtained. Among many methods for calculating coordination degree such as geometric method, variance method, weight mean method, the geometric method can be considered because of its simple computation and intuitional results and it can be expressed as follows:

$$CD = \frac{\min\left(\sum_{i=1}^{n} \omega_i u_j(e_{ji})\right)}{\left|\min\left(\sum_{i=1}^{n} \omega_i u_j(e_{ji})\right)\right|} \sqrt[J]{\prod_{j=1}^{J} \sum_{i=1}^{n} \omega_i u_j(e_{ji})} \tag{34}$$

where CD is the coordination degree; ω_i is the weight coefficient of $u_j(e_{ji})$ with $\omega_i > 0$, and $\sum_{i=1}^{n} \omega_i = 1$.

In this study, the optimal values of the six objectives are considered as the order parameters of the irrigation system based on the optimal water allocation results, among which WP and Gini coefficient are indexes of social dimension, net profit and economic benefit loss risk are indexes of economic dimension, and blue water utilization rate and leakage loss are indexes of resources dimension. These three dimensions, including social dimension, economic dimension and water resources dimension, make up a multi-dimensional system, and the coordination degree can reflect the coordinated development of these dimensions and can be considered as a measure of system sustainability. The larger the coordination degree, the stronger the sustainability, and vice versa.

3. Case study

3.1. Study site

The proposed model was utilized for the middle reaches of Heihe River basin. Heihe River basin is the second largest inland river basin in northwest China. Heihe River basin is divided into upper, middle and lower reaches, among which, the middle reaches (98°–101°30′E, 38°–42°N) that are between Yingluoxia hydrometric station and Zhengyixia hydrometric station are the main irrigated agricultural area, concentrating 90% of the total irrigation water use in the whole Heihe River basin. The middle reaches of Heihe River basin presents high evaporation (around 1410 mm each year) and low precipitation (around 140 mm each year), with the land area of 25.6 thousand km^2. There are 17 irrigation regions in the middle reaches of Heihe River basin, including Daman, Yingke, Xijun, Shangsan, Anyang, Huazhai, Pingchuan, Banqiao, Yanuan, Liaoquan, Shahe, Liyuanhe, Youlian, Liuba, Luocheng, Xinba, and Hongyazi irrigation regions (see Fig. 3). In order to ensure the ecological usage of water in the lower reaches of Heihe River basin, the agricultural water use in the middle reaches needs to reduce. Additionally, the uneven water distribution exacerbates water resources shortages in the middle reaches of Heihe River basin. Hence, optimization of limited water resources, including both surface water and groundwater, among different irrigation regions in the middle reaches of Heihe River basin is necessary. Fluctuating water availability and precipitation complicate optimization. Further, the problem concerning the sustainability, such as how to synthetically improve the benefit of social and economic benefit through appropriate utilization of water resources, arise. Such issues can be solved by the developed SMONLP model.

3.2. Data collection

Data for the SMONLP model mainly includes hydrological data for different irrigation regions and different time periods and socio-economic data for different irrigation regions.

3.2.1. Hydrological data

3.2.1.1. Grade specification of different runoff conditions. In this study, the grade specification of different conditions was based on runoff from Yingluoxia hydrological station from 1944 to 2014. When planning and managing water resources, it is necessary to select typical flow levels to reflect actual conditions more comprehensively. According to *Hydrological Basic Terminology and Symbol Standards* (National standard: GB/T50095-98), extreme wet, wet, normal, dry and extreme dry conditions can be used to reflect the dryness and wetness of river flow. Hence, five conditions of runoff were presented. Let P represent the frequency for dividing different flow levels, based on guaranteed rate method, $P \leq 12.5\%$ represents the extreme wet level ($h = 1$), $12.5\% < P \leq 37.5\%$ represents the wet level ($h = 2$), $37.5\% < P \leq 62.5\%$ represents the normal level ($h = 3$), $62.5\% < P \leq 87.5\%$ represents the dry level ($h = 4$), and $P > 87.5\%$ represents the extreme dry level ($h = 5$).

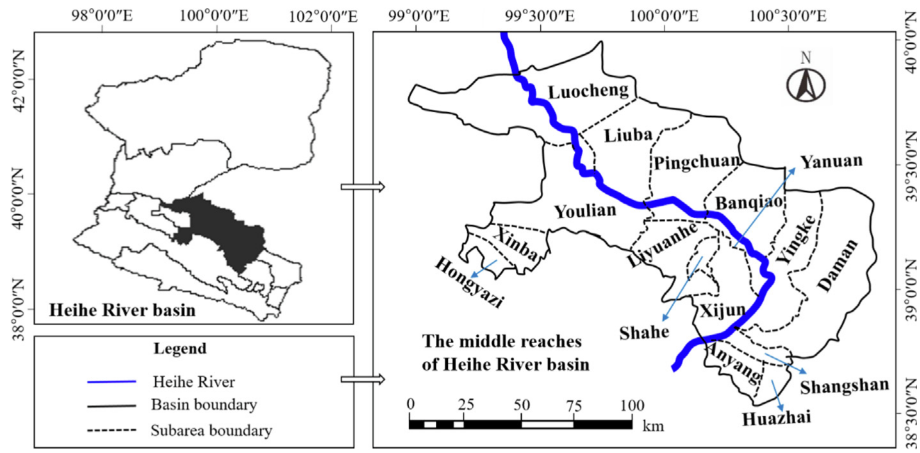

Fig. 3. A diagram of irrigation regions in the middle reaches of Heihe River basin.

Taking the runoff volume of Yingluoxia hydrological station from 1944 to 2014 as a data series, rank these data in descending order and the ranked series was recorded as $\{x_1, x_2, \cdots, x_m, \cdots, x_n\}$. Calculate the frequency using an empirical frequency formula that can be expressed as $P = (m/(n+1)) \times 100\%$, where m is the number of "greater than" and "equal to" x_m. On this basis, divide different flow levels based on the above categories of P, then the occurrence probability of each flow level was obtained by dividing the number of years of each flow level by the total number of years, as shown in Table 2.

3.2.1.2. Water availability. Water availability for the middle reaches of Heihe River basin includes surface water availability and groundwater availability. Surface water availability equaled the sum of runoff of Yingluoxia hydrological station, runoff of Liyuan River (the biggest tributary of Heihe River), and runoff of other small rivers minus runoff released to Zhengyixia hydrological station. Runoff of both Yingluoxia and Zhengyixia hydrological stations belongs to Heihe River. Compared with runoff from Heihe River, the runoff volume of other small rivers was quite small. Hence, the grade specification of different conditions of runoff from all the rivers were assumed as the same as runoff from Heihe River, actually from Yinluoxia hydrological station. Runoff data came from the observation data at hydrological stations. For the optimization model, crops in the middle reaches of Heihe River basin were classified as two types: food crops and commercial crops. For the study area, the cropped area of food crops accounted for about 85% of the total area, while the cropped area of commercial crops accounts for 15% of the total area. Food crops are the generic terms of grain crops, tuber crops and leguminous crops, and are generally used as staple food. In this study, food crops included field corn, forage corn and wheat. Commercial crops are also known as industrial crops, which are used to supply raw materials for industrial engineering, especially for light industry. In this study, commercial crops included vegetables, cotton and oil plant. The whole growing period including sowing, emergence and harvest of these crops is

Table 2
Basic data for water availability.

Item	Unit	Month	Flow levels				
			Extreme wet	Wet	Normal	Dry	Extreme dry
Runoff of Yingluoxia	$10^4 m^3$	April	7794.09	7779.64	6419.99	6952.30	5577.12
		May	13914.78	12889.38	10713.56	11000.57	8833.96
		June	26308.44	20230.96	21393.00	17709.84	12561.98
		July	48791.52	38218.96	34876.55	29876.21	23339.88
		August	43172.10	39221.54	29139.27	26641.09	24723.12
		September	30928.82	24847.60	21831.16	19222.46	17655.55
Runoff of Liyuanhe	$10^4 m^3$	April	1193.68	1189.48	992.81	1022.44	765.99
		May	2131.08	1970.75	1656.78	1617.80	1213.30
		June	4029.20	3093.25	3308.28	2604.50	1725.33
		July	7472.53	5843.56	5393.41	4393.74	3205.62
		August	6611.91	5996.85	4506.19	3917.97	3395.61
		September	4736.82	3799.12	3376.04	2826.95	2424.91
Runoff of other rivers	$10^4 m^3$	April	622.47	668.01	560.26	565.82	466.05
		May	1111.30	1106.76	934.95	895.29	738.21
		June	2101.12	1737.15	1866.91	1441.32	1049.75
		July	3896.72	3281.71	3043.59	2431.49	1950.41
		August	3447.93	3367.80	2542.91	2168.20	2066.00
		September	2470.12	2133.57	1905.15	1564.43	1475.40
Release water to Zhengyixia	$10^4 m^3$	April	6266.88	5570.94	4108.00	4027.97	1090.37
		May	3879.31	3600.49	308.39	113.32	125.84
		June	5424.19	2142.93	1534.72	998.62	2707.65
		July	25927.85	9664.68	13003.01	6105.15	6783.78
		August	6759.03	16483.85	7240.72	565.03	3301.02
		September	22480.95	20243.16	11648.58	15100.00	11750.00
Probability			0.1323	0.2085	0.3238	0.2205	0.1176

from early April to late September. Therefore, each month during the whole crop growing period was chosen as the time variable of this study. Various parts of water availability for the middle reaches of Heihe River basin during this period are given in Table 2.

3.2.1.3. Effective precipitation. The study area was located in the arid and semi-arid regions with the annual precipitation of less than 250 mm (140 mm in this study area), the empirical equation of effective precipitation by the USDA Soil Conservation method expressed as $P_{eff} = P\frac{125-0.2P}{125}$ when $P < 250$mm was used in this study, where P_{eff} is the effective precipitation (mm), and P is the precipitation (mm). The effective precipitation is shown in Table 3.

3.2.1.4. Water demand. Water demands per unit area for different irrigation regions and time periods was the numeric equivalent of crop actual evapotranspiration, which can be calculated by the crop coefficient approach and can be expressed as:

$$ET_c = k_c ET_0 \tag{35}$$

where ET_c is the daily crop evapotranspiration (mm); k_c is the crop coefficient; ET_0 is the daily reference crop evapotranspiration (mm), and the FAO-56 Penman-Monteith method was adopted to produce reasonable ET_0 which can be expressed as:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma[900/(T + 273)]u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{36}$$

where Δ is the slope of saturation vapor pressure versus air temperature (kPa/°C); R_n is the net radiation at the crop surface (MJ/(m^2·d); G is the soil heat flux density (MJ/(m^2·d); γ is the psychrometric constant (kPa/°C); T is the mean daily air temperature at 1.5–2.5 m height (°C); u_2 is the mean daily wind speed at 2 m height (m/s); e_s is the saturation vapor pressure (kPa); and e_a is the actual vapor pressure (kPa).

Water demand for different irrigation regions and time periods can be obtained by multiplying the corresponding water demands per unit area with irrigation areas of different crops. This study assumed that the net minimum water demand equaled a scaling factor multiplied the water demand, and the scaling factor was assumed 0.8. The value of the net minimum water demand was actually correlated to different crops, subareas, time periods and flow levels. However, the value which we used in Eq. (20) was the summation of different crops, leading to the net minimum water demand was related to different subareas, time periods and flow levels.

In this study, the value of monthly *VWC* for different crops was calculated by multiplying monthly ET_c (ET_c was related to different crops and time periods, see Table 3) and irrigation area (irrigation area was related to different crops, subareas and flow levels, see Table 5). Therefore, the value of *VWC* for different crops was various with crop types, subareas, time periods and flow levels. The value of VWC which was used in Eq. (7) was the summation of different crops. ET_c was calculated by the crop coefficient approach as Eq. (35) shows. The meteorological data for calculating ET_0, including temperature, wind speed, sunshine duration, relative humidity, air pressure, were from weather stations of Ganzhou County, Linze County and Gaotai County from meteorological observing networks of China. Ganzhou County, Linze County and Gaotai County are three main counties of Zhangye City, Gansu province, China, and all of the studied 17 irrigation regions are located in Zhangye City. Different crops correspond to different crop coefficients. For the middle reaches of Heihe River basin, field corn, forage corn, wheat, vegetables, cotton, and oil plants were considered. The data of crop coefficients for these crops were from Zhu (2015). The relative data for calculating water demand are given in Table 3.

3.2.2. Socio-economic data

For socio-economic data, the average values of yield per unit area, water utilization coefficients, costs, yield per unit water were acquired according to *Water Management Information Annual Report of Zhangye City* from 2010 to 2015. In this study, water utilization coefficients included the coefficients for canal irrigation and for field irrigation. Canal irrigation refers to the process that water form headwork is reasonably transported and distributed to each part of an irrigation district, mainly including trunk canal, branch canal, lateral canal and sub-lateral canal. Hence, the water utilization coefficient for canal irrigation reflects the water conveyance loss of all levels of canals from trunk canal to sub-lateral canal, and it can be estimated by the product of water utilization coefficients of all levels of canals. Field irrigation refers to that water is allocated to the filed through field ditch, furrow and corrugation to satisfy the needs for the normal growth of crops and soil requirement. Hence, the water utilization coefficient for field irrigation refers to the ratio of effective utilization amount of water in the field (i.e. the net irrigation amount) and the water that flows into the filed ditch (or furrow and corrugation). Detailed information of the water utilization coefficients for both canal irrigation and field irrigation can be seen in Table 4. The agricultural area for different irrigation regions was referred to Hao and Su, (2015) (see Table 5). The population data of the 17 irrigation regions was acquired from the local statistical yearbook. The minimum or the maximum water allocation amount was estimated by multiplying the minimum or the maximum water conveyance flow and filling time. The minimum and maximum water conveyance flows were assumed to be equal to 0.6 times and 1.2 times the design flow of the water conveyance canal of each irrigation region. Basic socio-economic data for different irrigation regions are given in Tables 4 and 5 For any irrigation district, the average benefit per unit yield was 1.67 Yuan/kg (Yuan is the monetary unit of China), food demand per capita was 400 kg, water supply and costs for surface water and groundwater were 0.05 Yuan/m^3 and 0.08 Yuan/m^3, respectively (Jiang et al., 2016).

Table 3
Basic data for effective precipitation and water demand.

Month	Average precipitation (mm)	Average ET_0 (mm)	Crop coefficient					
			Field corn	Forage corn	Wheat	Vegetables	Cotton	Oil plants
April	3.74	117.06	0.20	0.22	0.30	0.44	0.07	0.37
May	3.98	150.17	0.44	0.50	1.15	0.8	0.6	0.86
June	20.14	157.43	0.53	1.16	1.15	1	0.875	1.03
July	24.96	159.07	1.46	1.20	0.93	0.99	1.15	1.05
August	29.96	142.56	1.14	1.20		0.565	0.965	0.64
September	20.58	100.90	1.22	0.60		0.55	0.78	

Table 4
Basic data for different irrigation districts.

Irrigation districts	Population	Actual yield per unit area of food crops	Actual yield per unit area of commercial crops	Water utilization coefficient of canal irrigation	Water utilization coefficient of field irrigation	Cost	Specific yield	Minimum water allocation	Maximum water allocation
	Ten thousand	kg/ha	kg/ha	/	/	Yuan/m^3	/	10^4m^3	10^4m^3
Daman	7.65	13180	2250	0.65	0.84	0.0539	0.22	12060	24120
Yingke	16.44	12780	2250	0.73	0.78	0.0498	0.25	16595	33190
Xijun	7.20	12644	5085	0.67	0.84	0.0613	0.24	12924	25848
Shangsan	4.47	10530	3030	0.67	0.78	0.0820	0.24	5640	11280
Anyang	1.43	7740	2350	0.65	0.77	0.0657	0.10	1620	3240
Huazhai	0.88	6969	2242	0.62	0.82	0.1620	0.10	420	840
Pingchuan	2.02	12900	4917	0.65	0.84	0.0365	0.22	3480	8120
Banqiao	1.76	10200	3958	0.64	0.80	0.0434	0.12	3780	7560
Yanuan	1.14	9810	6192	0.58	0.84	0.0358	0.12	2042	4085
Liaoquan	1.77	10005	4989	0.64	0.80	0.0458	0.27	2011	4022
Shahe	4.08	9300	5100	0.81	0.84	0.0452	0.30	2100	4200
Liyuanhe	4.25	8455	4369	0.76	0.80	0.0551	0.24	9052	18103
Youlian	4.71	10135	4305	0.66	0.84	0.0477	0.25	18134	36268
Liuba	1.07	8940	3798	0.70	0.84	0.0593	0.15	2338	4675
Luocheng	1.38	11810	4095	0.61	0.80	0.0361	0.18	2830	8491
Xinba	1.49	7456	3899	0.67	0.80	0.0532	0.20	2700	4500
Hongyazi	0.67	7456	3433	0.66	0.76	0.0685	0.20	1320	2200

Table 5
Irrigation area under different conditions.

Irrigation districts	Irrigation area of food crops (10^4ha)					Irrigation area of commercial crops (10^4ha)				
	Extreme wet	Wet	Normal	Dry	Extreme dry	Extreme wet	Wet	Normal	Dry	Extreme dry
Daman	1.40	1.45	1.31	1.44	1.32	0.06	0.11	0.06	0.09	0.11
Yingke	1.30	1.19	1.38	1.33	0.99	0.24	0.25	0.25	0.25	0.20
Xijun	1.85	1.82	1.82	1.79	1.43	0.01	0.02	0.01	0.05	0.05
Shangsan	0.60	0.55	0.55	0.54	0.82	0.00	0.00	0.00	0.01	0.03
Anyang	0.07	0.14	0.08	0.08	0.27	0.07	0.10	0.11	0.08	0.07
Huazhai	0.08	0.07	0.06	0.06	0.12	0.01	0.02	0.01	0.01	0.04
Pingchuan	0.32	0.22	0.42	0.27	0.09	0.10	0.06	0.05	0.08	0.10
Banqiao	0.35	0.44	0.22	0.48	0.58	0.04	0.05	0.08	0.03	0.07
Yanuan	0.19	0.22	0.09	0.23	0.13	0.02	0.02	0.01	0.02	0.06
Liaoquan	0.26	0.32	0.19	0.23	0.29	0.04	0.08	0.04	0.05	0.09
Shahe	0.34	0.16	0.22	0.28	0.05	0.01	0.01	0.01	0.02	0.03
Liyuanhe	1.22	1.24	1.35	1.22	0.67	0.13	0.13	0.09	0.13	0.13
Youlian	1.05	0.94	1.07	1.07	1.06	0.37	0.39	0.39	0.41	0.32
Liuba	0.08	0.20	0.10	0.19	0.21	0.09	0.07	0.06	0.09	0.11
Luocheng	0.08	0.05	0.18	0.12	0.24	0.18	0.21	0.20	0.18	0.18
Xinba	0.17	0.11	0.30	0.21	0.09	0.07	0.10	0.10	0.10	0.07
Hongyazi	0.09	0.12	0.07	0.09	0.14	0.02	0.02	0.02	0.01	0.02

4. Analysis of results and discussion

4.1. Results of SMONLP model

The SMONLP model was solved based on the weighted minimum deviation method, thus, the weights of different objectives need to be set first. In order to avoid the subjective preference for different objectives, the same weights for different objectives were set, i.e. the weight of 0.1666 for each objective function was adopted in this study. By coding the developed SMONLP model in the optimization software, optimal water allocation results for different irrigation regions in different months during the whole crop growth period under different flow levels were obtained. Taking the normal flow level whose occurrence probability is the biggest (0.3238) as an example, the total water allocation results are shown in Fig. 4. It can be seen from the figure that among different months, June to August was the peak irrigation period, accounting for more than 70% of the total irrigation water allocation amount. Meanwhile, this period was also the critical period of crop growth that needed more water (73% of the water demand during the whole crop growth period was needed in this period). However, the

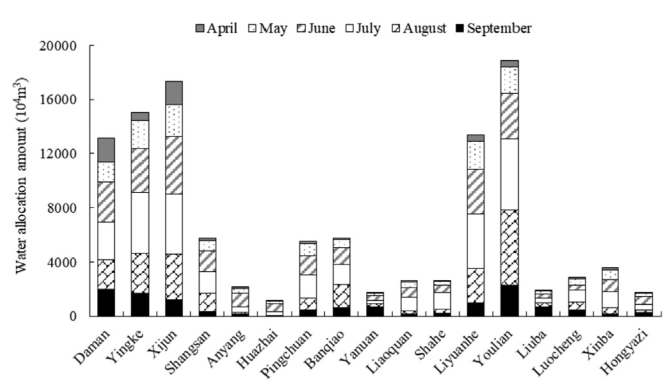

Fig. 4. Water allocation for different irrigation regions in different time periods.

vulnerability of water resources which can be defined by the water supply-demand ratio (Wu et al., 2013) of May is the largest. Larger vulnerability indicating the contradiction between supply and demand of water resources was comparatively more severe. In May,

water demand began to increase, however, the increase in the amplitude of water supply was smaller than that of water demand when compared with other months, leading to the larger vulnerability of water resources in May. Among different irrigation regions, the total water allocation amount of five irrigation regions exceeded 100 million m^3, the water allocation amounts of these five irrigation regions from high to low were Youlian, Xijun, Yingke, Liyuanhe, and Daman irrigation regions. The irrigation areas for these five irrigation regions in descending order were Xijun, Yingke, Daman, Youlian and Liyuanhe irrigation regions. There was no one-to-one correspondence between optimal water allocation amounts and irrigation areas of these five irrigation regions. In other words, larger irrigation areas may not correspond to larger water allocation amounts. Such results indicated that the water allocation scheme of the middle reaches of Heihe River basin no longer obeyed the traditional irrigation principle of "land decides water." The obtained water allocation schemes were the optimum results with various limiting factors being considered.

Fig. 5 shows optimal water allocation results including both surface water and groundwater for different irrigation regions under different flow levels. As shown in the figure, an unusual phenomenon occurred in that the total water allocation amount of extreme dry flow level was higher than extreme wet flow level. This was attributed to the groundwater availability. The total groundwater availability under extreme dry flow level was higher than that of extreme wet flow level within the allowable yield of groundwater. In fact, the optimal water allocation results, considering surface water availability, only basically followed natural laws. That is, water allocation under wetter flow levels were higher than that under drier flow levels, because wetter flow level corresponded to larger surface water availability. Specifically, the total water allocation amount under extreme wet flow level was the largest (10.32×10^8 m^3), total water allocation amount under middle flow level was intermediate (10.13×10^8 m^3), and total water allocation amount under extreme low flow level was the smallest (8.68×10^8 m^3). Results indicated that groundwater had the function of regulating water allocation schemes. Through the regulation of groundwater, the differences in the total water allocation amount between different flow levels were not significant. The figure also showed that the water allocation differences under different flow levels for some small irrigation regions were nearly the same. This was because the optimization model tended to satisfy the water demand of smaller irrigation regions, for it was easy to achieve. This could also cause that larger water shortage risks existed in larger irrigation regions.

The above analysis focused on total water allocation schemes, including both surface water and groundwater for different irrigation regions. However, the respective distribution of surface water and groundwater under different flow levels was also of interest to decision makers. Fig. 6 compares water allocation results of surface water and groundwater under seven conditions. "I" indicates the optimal results of the developed SMONLP model considering all of the six objectives. "O" indicates the optimal results of the developed SMONLP model considering one objective at a time and ignoring all other objectives. For example, "O-1" represents that only objective function 1, i.e. maximizing water productivity, was considered, and "O-2" represents that only objective function 2, i.e. minimizing Gini coefficient, was considered, and so on. The figure illustrates that the surface water allocation amount was much larger than the groundwater allocation amount. Surface water was still the main water supply for the middle reaches of Heihe River basin. It can be seen that the water allocation amount under "I" condition was in the range of maximum and minimum water allocation amounts, indicating that the "I" condition compromised among the six contradictory objective functions. By contrast, the water allocation amounts under "O-2" and "O-3" conditions were larger than that under other conditions in all flow levels except extreme dry flow level. This was concerned with the properties of objective functions. "O-2" and "O-3", respectively, represented the minimize Gini coefficient and maximize profit. For "O-2", the objective function tended to allocate more water for guaranteeing the equity of each irrigation region based on the form of this objective function. For "O-3", the profit equaled the total revenue minus total cost. Although allocating more water would lead to larger costs, the growth in total revenue was larger than the growth in water supply costs when more water was allocated in this study. Therefore, more water meant higher profit. For extreme dry flow level, the results inclined to ensure the minimum water demand, as the total surface water availability was the lowest, there was no extra water to be allocated. Fig. 6 also illustrates that the groundwater allocation amounts of "O-1" and "O-5" were smaller than for other conditions under different flow levels except extreme dry flow level. "O-1" was to maximize water productivity and "O-5" was to minimize the blue water utilization rate, the expressions of these two objective functions were inclined to allocate less water to increase water productivity and decrease the blue water utilization rate. Such results also indicated that these two objectives tended to prioritize surface water resources rather than groundwater resources.

One of the features of this article was to incorporate the economic benefit loss risk objective estimated by the CVaR model with confidence levels (α). Different confidence levels will result in different water allocation schemes and risk values (see Fig. 7). It should be noted that the choice of confidence level had a certain subjectivity without fixed rules, but confidence levels of larger than 0.5 were generally chosen (Li et al., 2015b; Soltani et al., 2016; Zhang et al., 2017). The figure shows that when the confidence level was larger than 0.8, the water allocation amount increased sharply after a stable situation. Then, as the confidence level increased, the water allocation amount continued to increase but the increasing amplitude was reduced. Meanwhile, the CVaR value kept increasing as the confidence level increased. The confidence level reflected the risk aversion of decision makers, as wetter flow levels indicated less risk acceptability and the tendency to account for bigger, less probable losses. The results were consistent with this law as expected.

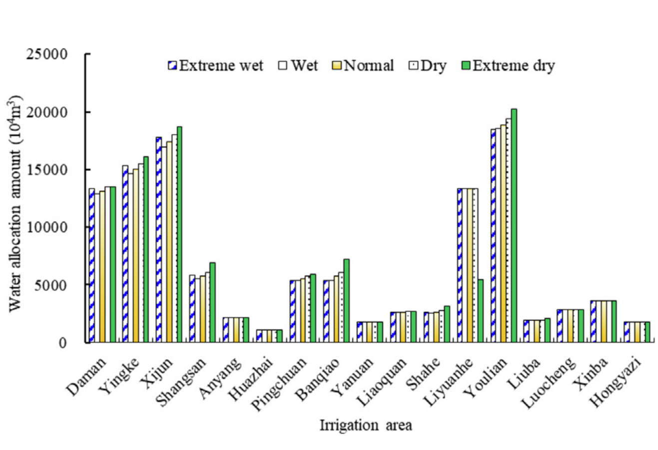

Fig. 5. Water allocation for different irrigation regions under different flow levels.

4.2. Scenarios analysis of the SMONLP model in a changing environment

Two scenarios were considered in this study, as shown in Fig. 1. The following analysis will focus on how the irrigation water allocation schemes change with the changes of risk probabilities and climate change.

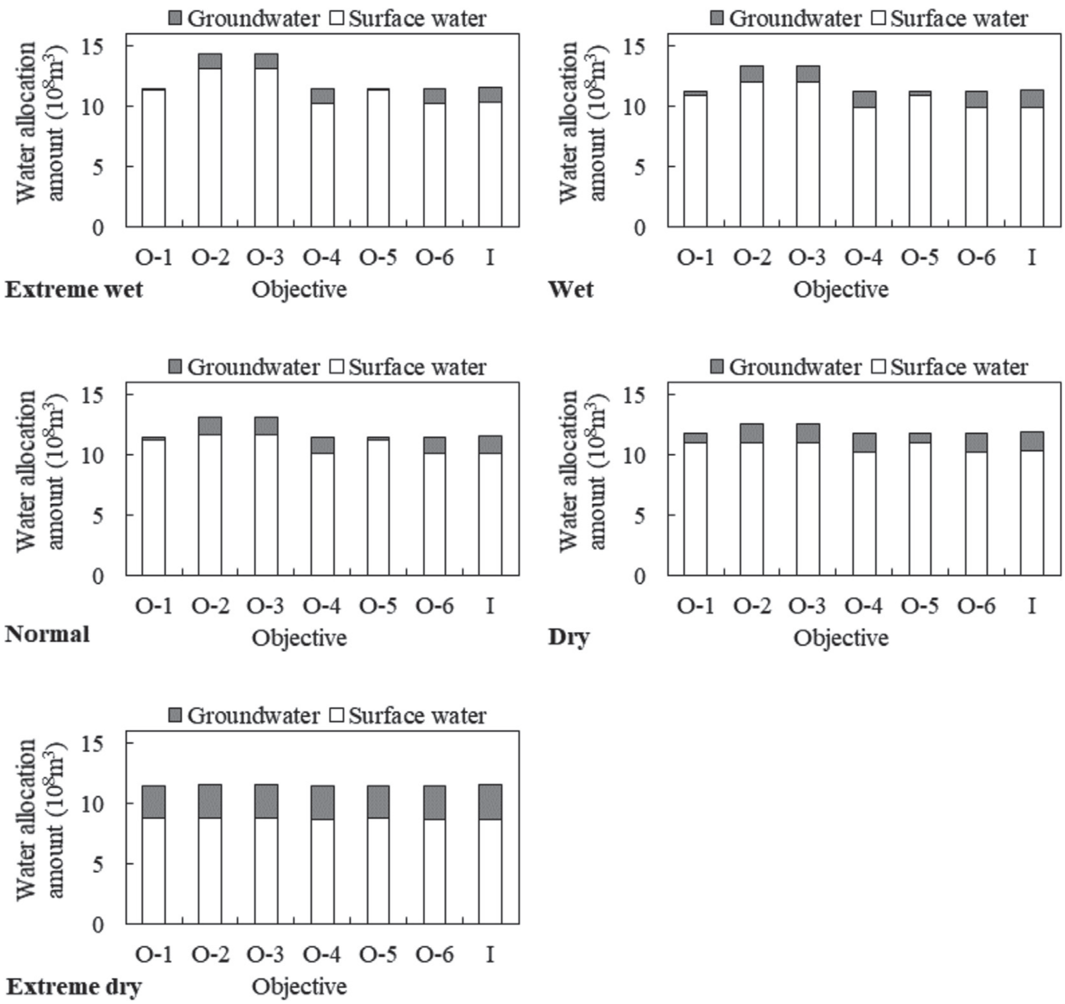

Fig. 6. Water allocation of different conditions under different flow levels.

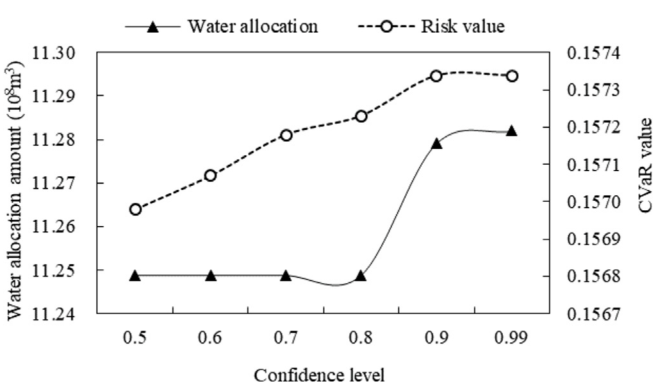

Fig. 7. Water allocation and CVaR values under different confidence levels.

4.2.1. *Results under different risk probabilities*

The developed SMONLP model was a stochastic model through incorporating CCP in the water availability constraint. The probability for the CCP constraint should be given first. Different probabilities meant different water availabilities, and thus would lead to different water allocation schemes. For this study, runoff amounts from Yingluoxia and Zhengyixia hydrological stations which were the two boundaries of the middle Heihe River basin were important components of water availability. Runoff from Yingluoxia hydrological station decided the water supply condition while the difference of runoff of Yingluoxia hydrological station and Zhengyixia hydrological station decided the water availability condition. Therefore, the changes of runoff from Yingluoxia hydrological station only and the changes of runoff from both Yingluoxia and Zhengyixia hydrological stations were both considered as scenarios in this part. Before explicating the runoff amounts under different probabilities, the probability distribution should be fixed in advance. For this study, five flow levels were considered which meant that the distribution of each of the five flow levels should be simulated. However, the historical data were not wholly adequate to simulate the probability distribution of each flow level. Therefore, Monte-Carlo stochastic simulation technique was adopted to generate more data. Person-III distribution which has been designated as the commonly used frequency curve in China (Gu et al., 2008) was adopted for stochastic simulation. The acceptance-rejection method was adopted for stochastically simulating the Person-III distribution. The acceptance-rejection method can be expressed as:

$$x_t = \alpha_0 + \frac{1}{\beta}\left[1 - \sum_{k=1}^{[\alpha]} \ln u_k - B_t \ln u_{|\alpha|+3}\right] \tag{37}$$

where $[\alpha]$ is the largest integer equal to or smaller than α; x_t is the t-th generated random number; u_k is the random number that is evenly distributed in the range of $[0, 1]$; $\bar{x}$, C_v, C_s are the average

value, variation coefficient, and skewness coefficient of random numbers, respectively; $u_{[\alpha]+1}$ and $u_{[\alpha]+2}$ are a couple of random numbers; $r = \alpha - [\alpha]$, and $s = 1 - r$.

Simulation was conducted 1000 times and the probability distributions under different flow levels were obtained, from which the specific values corresponding to each probability were acquired, as shown in Fig. 8 (Taking wet, normal and dry flow levels as examples). On this basis, the CCP constraint was transformed into a deterministic constraint.

Based on the stochastic simulation, the minimum and maximum results for each objective function under different probabilities, considering the changes of runoff from Yingluoxia hydrological station only (Y) and the changes of runoff from both Yingluoxia and Zhengyixia hydrological stations (Y-Z), were obtained, as shown in Fig. 9. Larger probabilities mean more water was available. Under Y scenario, as the changes of runoff from Zhengyixia hydrological station were not considered, larger probabilities mean more water can be used by the irrigation regions in the middle reaches of Heihe River basin according to CCP. Under "Y-Z" scenario, as the changes of runoff from both Yingluoxia and Zhengyixia hydrological stations were considered, larger probabilities mean more water from Yingluoxia hydrological station, and also more water will be released from Zhengyixia to the lower reaches of Heihe River basin, leading to smaller differences between Yingluoxia and Zhengyixia hydrological stations. In other words, under such a scenario, the water availability for the middle reaches of Heihe River basin was smaller than under "Y" scenario. For WP objective, as the definition of water productivity illustrated, the objective function value decreased as the probabilities increased under the "Y" scenario, because more water availability meant more water allocation, and thus would lead to lower water productivity. On the contrary, the objective function value increased as the probabilities increased under the "Y-Z" scenario because less water availability meant less water allocation, and higher water productivity was obtained. A similar phenomenon also happened for the profit objective function, blue-water utilization ratio objective function and leakage objective function. This is because higher water allocation corresponding to "Y" scenario will lead to higher profit, larger blue-water utilization ratio and larger leakage, while less water allocation corresponding to "Y-Z" scenario will lead to lower profit, smaller blue-water utilization ratio and smaller leakage. For Gini coefficient objective function, the objective function value increased first and then decreased sharply as the probability increased under "Y" scenario while the objective function value decreased first and then increased sharply as the probability increased under "Y-Z" scenario. This indicated that the allocation equity decreased first and then increased under "Y" scenario, while the allocation equity increased first and then decreased under "Y-Z" scenario. The break point occurred at the probability of 0.3. The water allocation equity stayed stable between probabilities of 0.1 and 0.25. The figure also shows that all the values of the Gini coefficient under different probabilities were below 0.4, i.e. the security line of equity (Zhang and Xu, 2011), indicating that the optimal allocation results guaranteed the social stability of the studied agricultural irrigation system. For economic benefit loss risk objective, the changes of probabilities of both "Y" and "Y-Z" scenarios had a negligible effect on the changes of economic benefit loss risk levels. Decision makers can choose suitable water allocation schemes according to different practical demands. For example, if water allocation equity was preferred, considering the changes of runoff from both Yingluoxia and Zhengyixia hydrological stations, the water allocation schemes corresponding to the probability of 0.25 was chosen because at this point, the equity of water allocation achieved the optimal status. However, larger probabilities indicated more risk of water shortages and thus the consequent penalty of water shortage had been produced.

Among all the wet and dry levels of runoff, the extreme dry level was the most unfavorable level for water allocation, because water availability under this level was the lowest. Thus, taking the extreme dry level as an example, Fig. 10 illustrates the changes of water allocation under different probabilities in each month. It was obvious that there occurred changes of water allocation under different probabilities under each month. For example, in April and August, the water allocation amount increased as the probability increased, in May, July and September, the water allocation amount decreased as the probability increased, and in June, the water allocation amount fluctuated as the probability increased. All these results depended on the difference of runoff from Yingluoxia and Zhengyixia hydrological stations corresponding to different probabilities.

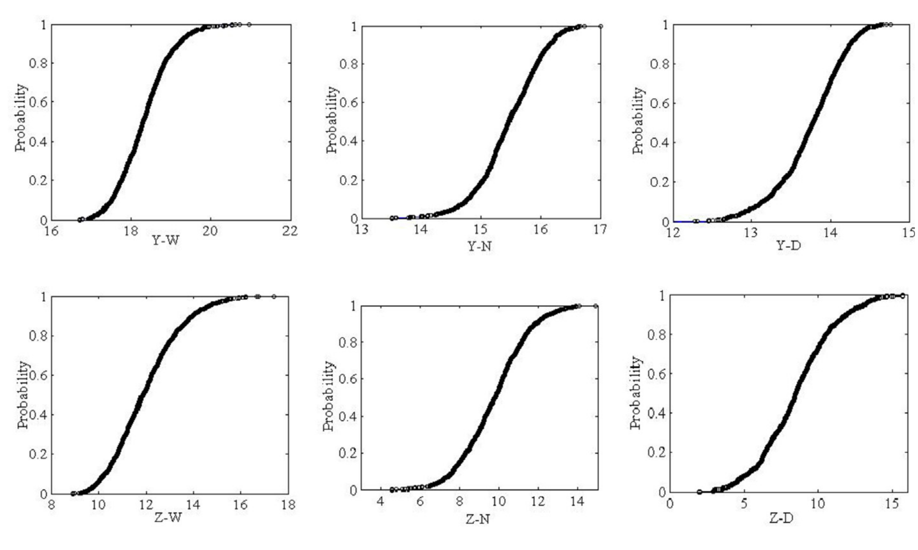

Fig. 8. Probability distribution of runoff from Yingluoxia and Zhengyixia hydrological stations.
Note: Y-W means runoff from Yingluoxia in wet flow level; Y-N means runoff from Yingluoxia in noraml flow level; Y-D means runoff from Yingluoxia in dry flow level; Z-W means runoff from Zhengyixia in wet flow level; Z-N means runoff from Zhengyixia in normal flow level; Z-D means runoff from Zhengyixia in dry flow level; The unit of all the values is 10^8 m^3.

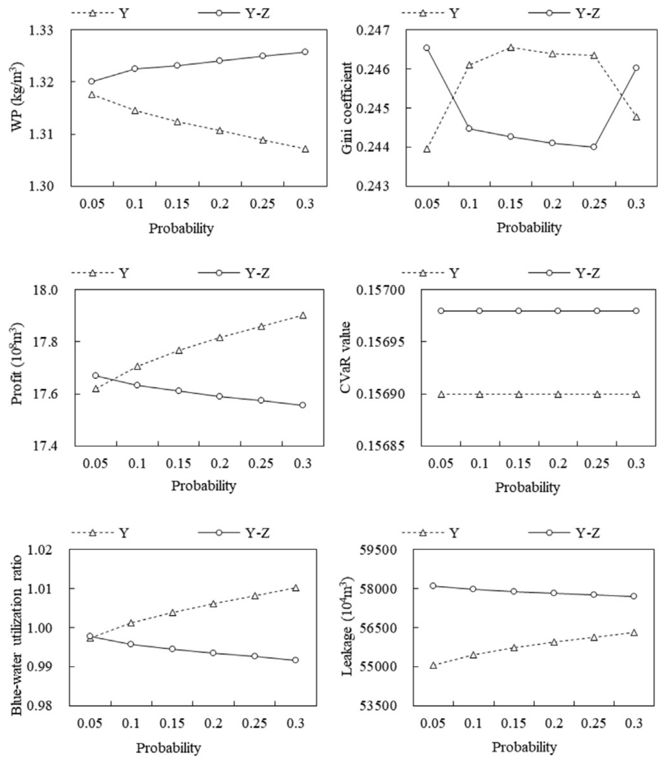

Fig. 9. Objective values under different probabilities.
Note: Y means scenario considering the changes of runoff from Yingluoxia hydrological station only; Y-Z means scenario considering the changes of runoff from both Yingluoxia and Zhengyixia hydrological stations.

4.2.2. Results considering climate change

Climate change was expected to affect water supply and demand, and thus water allocation schemes were affected. Various emission scenarios were set using a global system model for the prediction of climate change. The fifth report of IPCC (2013) provided a new scenario for greenhouse gas emission called Representative Concentration Pathways (RCP). RCP scenario emphasizes the comprehensive outcome of emission path and equivalent carbon dioxide concentration of various greenhouse gases and aerosol aiming at radiative forcing and concentration. Four scenarios were included in the RCP scenario, they were RCP 8.5, RCP 6.0, RCP 4.5 and RCP 2.6. Among them, RCP 8.5 is a high-end path, RCP 2.6 is a low-end path, and RCP 6 and RCP 4.5 are stable path between RCP 8.5 and RCP 2.6. RCP 4.5 is generally used with priority (Richard et al., 2010; Xu and Xu, 2012), therefore, this study chose RCP 4.5 scenario to analyze the changes of optimal water allocation schemes of the developed SMONLP model. The meteorological data from Global Climate Model cannot be used directly. This study used the data compiled for Heihe River basin by Xiong and Yan (2013). For this study, the climate change affected the water allocation scheme through the changes of precipitation and evapotranspiration that were influenced by the changes of meteorological elements. The precipitation of Ganzhou, Linze and Gaotai counties from 2021 to 2050 were 123 mm, 105 mm and 103 mm, respectively. The precomputed evapotranspiration of Ganzhou, Linze and Gaotai counties were 998 mm, 861 mm and 806 mm, respectively. Ganzhou county contained Daman, Yingke, Xijun, Shangsan, Anyang and Huazhai irrigation regions, Linze county contained Pingchuan, Banqiao, Yanuan and Liaoquan irrigation regions, and Gaotai county contained Youlian, Liuba, Xinba, and Hongyazi irrigation regions. Based on these data, the optimal results of the SMONLP model were obtained and comparison with the results of current condition, i.e. the results of the SMONLP model using current and historical data is shown in Fig. 11. Compared with the current condition, the water allocation of each irrigation region in each month under the scenario of RCP 4.5 had changed. The total water allocation amount of RCP 4.5 increased slightly. From April to September, the total water allocation under RCP 4.5 decreased by 4.24%, increased by 10.64%, increased by 2.87%, increased by 2.27%, increased by 3.51%, and decreased by 21.48% compared with the current condition. The changes in amplitude in September was the largest. By comparison, if only the changes of precipitation and evapotranspiration were considered, the water allocation amount in the future would largely remain unchanged. Therefore, the water allocation amount under the current condition can offer a certain guidance for water allocation in the future.

4.3. Sustainability analysis

In this study, the optimal values of the six objective functions were the order parameters of the agricultural irrigation system based on the optimal water allocation results. Three dimensions, including social dimension (WP and Gini coefficient), economic dimension (profit and economic benefit risk), and water resources dimension (blue water utilization rate and leakage loss) were considered. The maximum and minimum values of each index in each dimension were obtained by solving one objective function only by maximizing and minimizing the objective functions ignoring the other objective functions of the SMONLP model, while the optimal value was the comprehensive optimal result of the

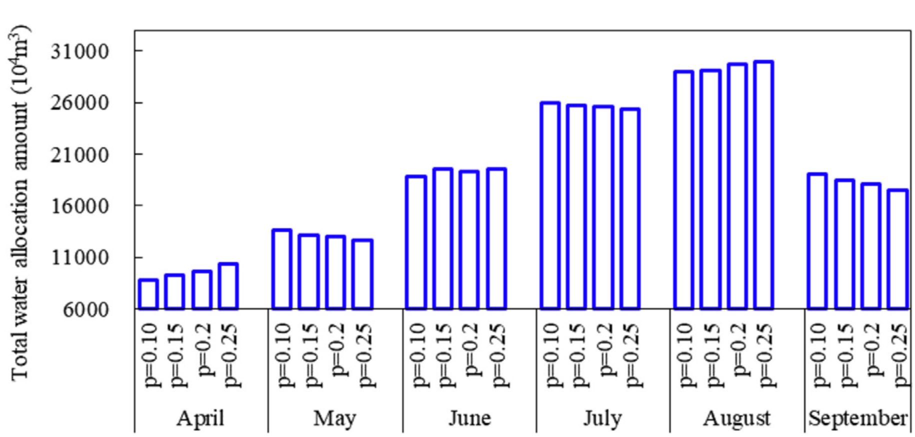

Fig. 10. Water allocation amount under different probabilities.

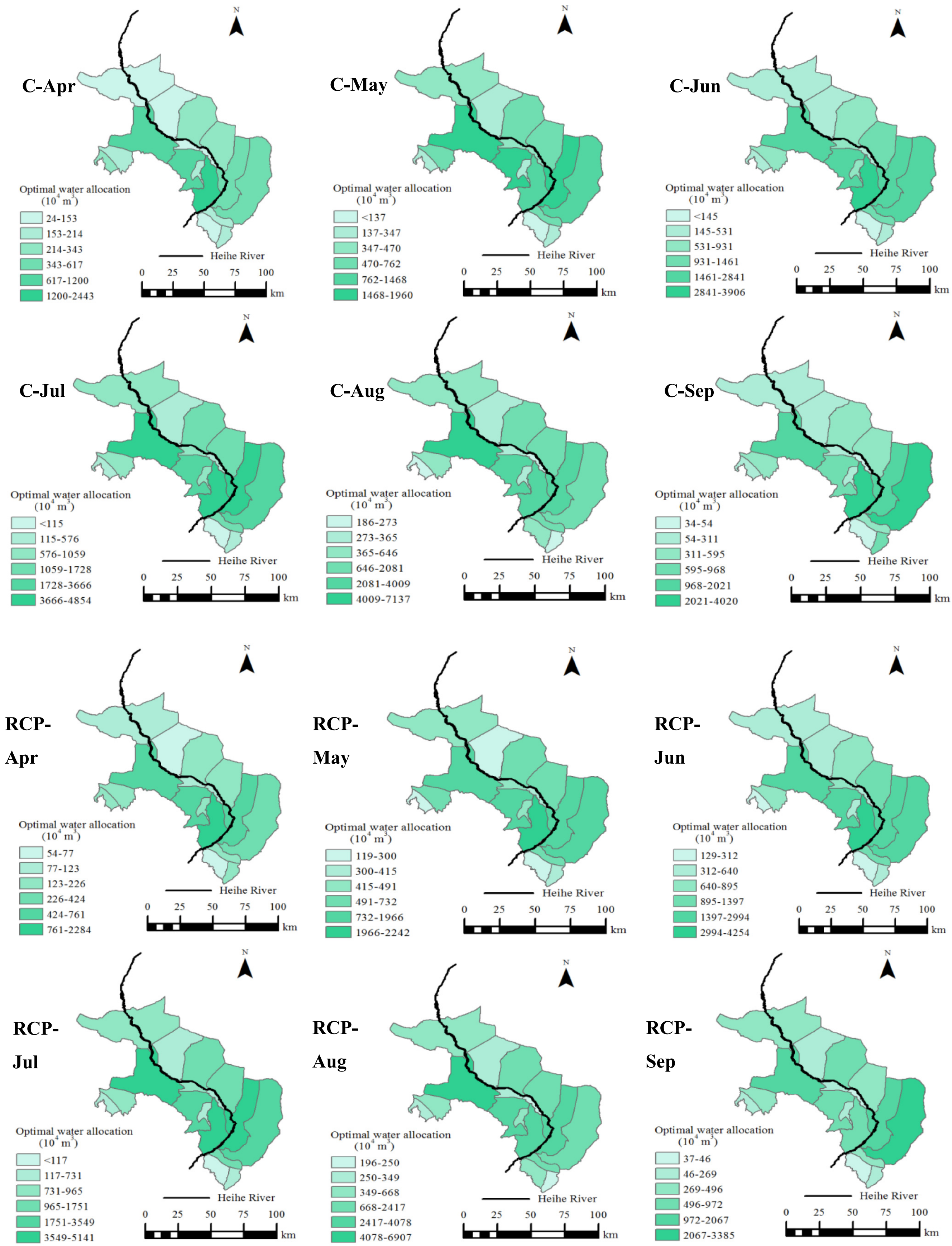

Fig. 11. Comparison of water allocation between RCP 4.5 and current conditions.

Table 6
Order degree and coordination degree of different scenarios.

Scenario	Order degree			Coordination degree
	Society	Economy	Water resources	
Current condition	0.3533	0.8533	0.6005	0.7105
CCP-0.1	0.3589	0.8629	0.5945	0.7129
RCP4.5	0.3053	0.9042	0.4999	0.6729

SMONLP model simultaneously considering the six objectives. Three scenarios, including the current condition, the CCP constraint under the probability of 0.1, and RCP 4.5 were considered. After calculating the order parameter of each index in each dimension, the order degree of each dimension and the coordination degree of the three scenarios are given in Table 6. The order degree was expressed as the weights multiplied by the order parameter of indexes in each dimension. The weight of each index was set 0.5 in each dimension. As shown in Table 6, the coordination degrees of the three scenarios were around 0.7, indicating that the coordination of the system was relatively good, because the developed model simultaneously considered many aspects associated with society, economy, and resources. This revealed that the irrigation system based on the optimal results was relatively sustainable. Through intercomparison of the three scenarios, the scenario considering the CCP constraint with the probability of 0.1 had a larger coordination degree than did the other two scenarios. The scenario of RCP 4.5 experienced the lowest coordination degree, mainly because the contradiction in water supply-demand was exacerbated. Therefore, for irrigation water allocation in the future, improving water use efficiency was still the research priority.

5. Conclusion

This paper developed a stochastic multi-objective non-linear programming (SMONLP) model for sustainable irrigation in a changing environment. Three advantages that make the developed model unique by comparison with previous methods in agricultural water management are: (1) The SMONLP model balances the competing goals associated with social, economic, and resources dimensions that are interactive in an agricultural irrigation system, which will be conducive to the sustainable allocation of irrigation water resources. (2) The SMONLP model considers the response of water resources allocation to the randomness of water availability and climate change, which will help gain insights in the changing trend of water resources allocations under a changing environment, thus contributing to the planning of water resources. (3) Various water allocation schemes were evaluated based on the synergetic theory from the viewpoint of sustainable development which will help decision makers make appropriate selections. The SMONLP model effectively integrated linear programming, fractional linear programming, nonlinear programming, and chance constrained programming into a multi-objective programming framework based on the methodology of optimal allocation, equality expressed as Gini coefficient, risk control expressed as CVaR, and virtual water expressed as blue water utilization rate, investigating the interactive effects of varied water allocation process including water supply, water conveyance, water demand, and water utilization.

The SMONLP model was applied to an agricultural irrigation system in northwestern China to demonstrate its applicability. The weighted minimum deviation method was used to solve the model. Its solutions provide tradeoff strategies with explicit society-economy-resources information regarding the combination of surface water and groundwater under uncertainty. The solution alternatives were analyzed and compared to identify desired water resources allocation schemes, and water resources allocation in different growth stages of crops facilitate dynamic irrigation water management. Comparison shows that the coordination degree of water allocation decreased in RCP 4.5 is mainly attributed to the aggravated contradiction between water supply and demand. Therefore, improving water use efficiency would still be a major concern in an agricultural irrigation system.

The developed model is applicable to and recommended for wide-scale applications in the world with similar optimization problems. For its applications to other areas or scales, the model formulation can be easily modified according to specific circumstances. This paper attempted to comprehensively explore the allocation of irrigation water considering the interaction of the society-economy-resources system. Although the model can generate allocation schemes under a changing environment, the uncertainties expressed as randomness can be expressed. However, more uncertainties, not merely randomness, exist in an agricultural irrigation system which make the problem more complex, and this deserves further study in order to enhance the applicability of the model.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (No. 51809040, 91425302, 51709195), National Science Fund for Distinguished Yong Scholars of China (51825901), and Natural Science Foundation of Heilongjiang Province of China (E2018004).

References

Abdulbaki, D., AI-Hindi, M., Yassine, A., Najm, M.A., 2017. An optimization model for the allocation of water resources. J. Clean. Prod. 164, 994–1006.
Cai, X.M., McKinney, D.C., Lasdon, L.S., 2002. A framework for sustainability analysis in water resources management and application to the Syr Darya Basin. Water Resour. Res. 138 (6), 21, 14pages.
Dai, C., Qin, X.S., Chen, Y., Huo, H.C., 2018. Dealing with equality and benefit for water allocation in a lake watershed: a Gini-coefficient based stochastic optimization approach. J. Hydrol. 561, 322–334.
Divakar, L., Babel, M.S., Perret, S.R., Gupta, A.D., 2011. Optimal allocation of bulk water supplier to competing use sectors based on economic criterion-an application to the Chao Phraya River basin, Thailand. J. Hydrol. 40 (1–2), 22–35.
Fasakhodi, A.A., Nouri, S.H., Amini, M., 2010. Water resources sustainability and optimal cropping pattern in farming system: a multi-objective fractional goal programming approach. Water Resour. Manag. 24, 4639–4657.
Geerts, S., Raes, D., 2009. Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas. Agric. Water Manag. 96, 1275–1284.
Georgiou, P.E., Papamichail, D.M., 2008. Optimization model of an irrigation reservoir for water allocation and crop planning under various weather conditions. Irrig. Sci. 26 (6), 487–504.
Gu, W.Q., Shao, D.G., Huang, X.F., Dai, T., 2008. Multi-objective risk assessment on water resources optimal deployment. J. Hydraul. Eng. 39 (3), 338–345.
Gurav, J.B., Regulwar, D.G., 2012. Multi objective sustainable irrigation planning with decision parameters and decision variables fuzzy in naturel. Water Resour. Manag. 26, 3005–3021.
Guo, P., Huang, G.H., 2009. Two-stage fuzzy chance-constrained programming: application to water resources management under dual uncertainties. Stoch. Environ. Res. Risk Assess. 23, 349–359.
Guo, P., Huang, G.H., Li, Y.P., 2010. An inexact fuzzy-chance-constrained two-stage mixed-integer linear programming approach for flood diversion planning under multiple uncertainties. Adv. Water Resour. 33, 81–91.
Guo, P., Wang, X.L., Zhu, H., Li, M., 2014. Inexact fuzzy chance-constrained nonlinear

programming approach for crop water allocation under precipitation variation and sustainable development. J. Water Resour. Plan. Manag. 140 (9), 05014003.
Hao, L.N., Su, X.L., 2015. Determination for suitable scale of oasis and cultivated land in middle reaches of Heihe River basin. Trans. Chin. Soc. Agric. Eng. 31 (10), 262–268 (in Chinese with English abstract).
Huang, G.H., 1998. A hybrid inexact-stochastic water management model. Eur. J. Oper. Res. 107 (1), 137–158.
Huang, Q., Chang, J.X., 2007. The Theories and Methods of Water Resources Multi-Dimensional Critical Regulation and Control. China Water Power Press, Beijing.
Hu, Z.N., Wei, C.T., Yao, L.M., Li, L., Li, C.Z., 2016. A multi-objective optimization model with conditional value-at-risk constraints for water allocation equality. J. Hydrol. 542, 330–342.
IPCC, 2013. Climate change 2013: the physical science basis. In: Sttocker, T.F., Qin, D., Plattner, G.-K., et al. (Eds.), Contribution of Working GroupIto the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, p. 1535.
Jiang, Y., Xu, X., Huang, Q.Z., Huo, Z.L., Huang, G.H., 2016. Optimization regional irrigation water use by integrating a two-level optimization model and an agro-hydrological model. Agric. Water Manag. 178, 76–88.
Kang, Y.H., Khan, S., Ma, X.Y., 2009. Climate change impacts on crop yield, crop water productivity and food security-A review. Prog. Nat. Sci. 19 (12), 1665–1674.
Li, M., Fu, Q., Singh, V.P., Ma, M.W., Liu, X., 2017. An intuitionistic fuzzy multi-objective non-linear programming model for sustainable irrigation water allocation under the combination of dry and wet conditions. J. Hydrol. 555, 80–94.
Li, M., Fu, Q., Singh, V.P., Ji, Y., Liu, D., Zhang, C.L., 2019. An optimal modelling approach for managing agricultural water-energy-food nexus under uncertainty. Sci. Total Environ. 651, 1416–1434.
Li, M., Fu, Q., Singh, V.P., Liu, D., 2018. An interval multi-objective programming model for irrigation water allocation under uncertainty. Agric. Water Manag. 196, 24–26.
Li, M., Guo, P., 2014. A multi-objective optimal allocation model for irrigation water resources under multiple uncertainties. Appl. Math. Model. 38, 4897–4911.
Li, M., Guo, P., Zhang, L.D., Zhao, J.M., 2015a. Multi-dimensional critical regulation control modes and water optimal allocation for irrigation system in the middle reaches of Heihe River basin, China. Ecol. Eng. 76, 166–177.
Li, W., Wang, B., Xie, Y.L., Huang, G.H., Liu, L., 2015b. An inexact mixed risk-aversion two-stage stochastic programming model for water resources management under uncertainty. Environ. Sci. Pollut. Res. 22, 2964–2975.
Liu, J., Li, Y.P., Huang, G.H., Zhuang, X.W., Fu, H.Y., 2017. Assessment of uncertainty effects on crop planning and irrigation water supply using a Monte Carlo simulation based dual-interval stochastic programming method. J. Clean. Prod. 149, 945–967.
Norry, H., Liaghat, A.M., Parsinejad, M., Haddad, O.B., 2012. Optimizing irrigation water allocation and multicrop planning using discrete PSO algorithm. J. Irrig. Drain. Eng. 138 (5), 437–444.
Ren, C.F., Guo, P., Tan, Q., Zhang, L.D., 2017. A multi-objective fuzzy programming model for optimal use of irrigation water and land resources under uncertainty in Gansu Province, China. J. Clean. Prod. 164, 85–94.
Richard, M., Jae, E., Kathy, H., Martin, R.M., Steven, K.R., Detlef, P.V., Timothy, R.C., Seita, E., Mikiko, S., Tom, K., Gerald, A.K., John, F.B.M., Nebojsa, N., Keywan, R., Steven, J.S., Ronald, J.S., Allison, M.T., John, P.W., Thomas, J.W., 2010. The next generation of scenarios for climate change research and assessment. Nature 463 (7282), 747–756.
Rockafellar, R.T., Uryasev, S., 2000. Optimization of conditional value-at-risk. J. Risk 2 (3), 21–41.
Rost, S., Gerten, D., Bondeau, A., Lucht, W., Rohwer, J., Schaphoff, S., 2008. Agricultural green and blue water consumption and its influence on the global water system. Water Resour. Res. 44 (9), W09405.
Shahid, S., 2011. Impact of climate change on irrigation water demand of dry season *Boro* rice in northwest Bangladesh. Clim. Change 105, 433–453.
Singh, A., 2014. Irrigation planning and management through optimization modelling. Water Resour. Manag. 28 (1), 1–14.
Soltani, M., Kerachian, R., Nikoo, M.R., Norry, H., 2016. A conditional value at risk-based model for planning agricultural water and return flow allocation in river systems. Water Resour. Manag. 30, 427–443.
Su, X.L., Li, J.F., Sing, V.P., 2014. Optimal allocation of agricultural water resources based on virtual water subdivision in Shiyang River Basin. Water Resour. Manag. 28, 2243–2257.
Sun, W., Huang, G.H., Lv, Y., Li, G.C., 2013. Inexact joint-probabilistic chance-constrained programming with left-hand-side randomness: an application to solid waste management. Eur. J. Oper. Res. 228, 217–225.
Wu, G., Li, L., Ahmad, S., 2013. A dynamic model for vulnerability assessment of regional water resources in arid areas: a case study of Bayingolin, China. Water Resour. Manag. 27 (8), 3085–3101.
Xiong, Z., Yan, X., 2013. Building a high-resolution regional climate model for the Heihe River Basin and simulating precipitation over this region. Chin. Sci. Bull. 58 (36), 4670–4678.
Xu, C.H., Xu, Y., 2012. The projection of temperature and precipitation over China under RCP scenarios using a CMIP5 multi-model ensemble. Atmos. Ocean. Sci. Lett. 5 (6), 527–533.
Yang, G.Q., Guo, P., Huo, L.J., Ren, C.F., 2015. Optimization of the irrigation water resources for Shijin irrigation district in north China. Agric. Water Manag. 158, 82–98.
Zhao, J.M., Li, M., Guo, P., Zhang, C.L., Tan, Q., 2017. Agricultural water productivity oriented water resources allocation based on the coordination of multiple factors. Water 9 (7), 490, 22pages.
Zhang, C.L., Guo, P., 2018. An inexact CVaR two-stage mixed-integer linear programming approach for agricultural water management under uncertainty considering ecological water requirement. Ecol. Indicat. 92, 342–353.
Zhang, C.L., Li, M., Guo, P., 2017. An interval multistage joint-probabilistic chance-constrained programming model with left-hand-side randomness for crop area planning under uncertainty. J. Clean. Prod. 167 (20), 1276–1289.
Zhang, P., Xu, M., 2011. The view from the county: China's regional inequalities of socio-economic development. Ann. Econ. Finance 12 (1), 183–198.
Zhi, Y., Yin, X.A., Yang, Z.F., 2016. Assessing the changes of China's virtual water exports in 2002 and 2007. J. Environ. Inform. 27 (1), 43–51.
Zhu, H., Huang, G.H., 2011. SLFP: a stochastic linear fractional programming approach for sustainable waste management. Waste Manag. 31, 2612–2619.
Zhu, J.F., 2015. Water Cycle Evolution and Response Characteristics to Water Scheduling in Middle-Lower Heihe River Basin. Doctoral thesis. Tsinghua University, Beijing.